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Research Proposal Letter for Ph.D. (ABM)`

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9. Introduction

Blockchain, introduced by Satoshi Nakamoto in 2008 and implemented through Bitcoin in 2009, enabled secure and decentralized digital transactions and later expanded to various applications beyond cryptocurrency. The concept of smart contracts, proposed by Nick Szabo in 1994, allows automated, self-executing agreements without intermediaries. Over time, innovations such as Proof of Stake (PoS) have been developed to improve efficiency compared to Proof of Work (PoW). However, blockchain still faces some limitations, such as slower transaction speeds due to the need for network-wide validation, although these can be addressed through scaling solutions (Komalavalli, 2020).

Blockchain technology is rapidly gaining importance across various industries because of its decentralized, transparent, and secure nature. It offers advantages like improved efficiency, lower costs, and better traceability. Although it was first widely used in finance and banking, its applications have now expanded to areas such as supply chain, healthcare, energy, insurance, and real estate (Baiod et al., 2021).

It combines technologies such as hash algorithms, asymmetric cryptography, timestamps, and consensus mechanisms. Key features of blockchain include decentralization, security, transparency, traceability, and programmability (Xinyi et al., 2018). The blockchain system generally consists of three main layers: the protocol layer network and application layers. The protocol layer is where the technology's code and core functionalities such as data structures and consensus processes are constructed. It houses the computer power and serves as the foundation for next two layers. The network layer is where the ledger replications are kept. The application layer is where apps are created and a product digital profile is set up for configuration in blockchain network (Bakre *et al.*, 2017). Based on data accessibility, blockchain can be classified into four types- Public blockchain where anyone can read and submit transactions; Private blockchain, where access is restricted to a single organization or its group; Consortium (community) blockchain, where multiple organizations share control and access and Hybrid blockchain, which combines features of public, private or consortium systems to allow flexible, multi-mode operation (Lin and Liao, 2017).

Blockchain technology is increasingly being applied in the agriculture sector, offering benefits such as improved food safety through better traceability of product origin, efficient information systems, smoother agricultural trade, access to finance, crop certification and insurance services. It has potential to support various stakeholders, especially farmers, who are often disadvantaged due to multiple challenges (Yadav and Singh, 2019). Moreover, blockchain can be used in several areas, including land management, maintaining land records, tracking purchase details, monitoring the use of farm equipment and pesticides, handling financial transactions, and ensuring transparency in traceability systems across the agriculture supply chain (Maru *et al.*, 2018).

This technology has connect to the circular economy it can also improve the sustainability factor in agricultural supply chain (Jabbour *et al.*, 2017) Blockchain is known to offer transparency in a firm value chain and promotes the reliable data collection and transactions on a real—time basis. These aspect helps in making data-driven decisions (Xiong *et al.*, 2010) Thus, fraud and malpractices can be reduced through smart contracts (Sylvester 2019). Together these benefits contribute to enhancing the overall sustainability of the agri supply chain (Li and Wang, 2018).

Blockchain technology supports sustainability by reducing the role of intermediaries and giving equal opportunities to small stakeholders. It allows farmers to make better decisions about what crops to grow and when to sell them, making agriculture more efficient and

resilient. It also encourages practices like community farming, which help shorten the supply chain. With better access to information, consumers can buy fresh, seasonal, and locally produced food at fair prices. By building digital trust between producers and consumers, blockchain also helps lower transaction costs (Yiannas, 2018).

The adoption of blockchain in agricultural supply chains is influenced by several important factors. Smart contracts ensure timely payments once delivery is confirmed, helping to solve common payment delays (Saberi et al., 2019). Blockchain also provides reliable proof of organic or ethical production, enabling farmers to get better prices and access international markets (Chiaraluce et al., 2024). In addition, it reduces paperwork and simplifies verification processes, lowering administrative costs. Real-time tracking improves transparency, reduces the chances of food fraud and mislabelling, and helps protect the reputation of traders dealing with perishable products (Antonucci et al., 2019).

The availability of financial resources, technical expertise and management support are pivotal internal drivers (Munyanyi *et al.,* 2025).Governmental guidelines and subsidies significantly enhance the perceived usefulness of blockchain, acting as a catalyst for industry wide adoption (Dugyala *et al.,* 2024).

Blockchain adoption faces several challenges. One major issue is the high implementation cost, which includes investment in digital infrastructure, training and system maintenance, making it difficult for smallholder farmers to participate (Kshetri, 2017). Additionally limited technical knowledge and less digital literacy in rural stakeholders hinder effective utilization of blockchain systems (Yadav and Singh, 2020). Poor internet connectivity and inadequate digital infrastructure in village areas further restrict adoption (Tripoli and Schmidhuber, 2018).

Cotton is key economic fibre, accounting for about 40 percent of the total fibre used in the textile industry in 2004 (Wakelyn *et al.*, 2006). It is cultivated worldwide and thrives particularly well in regions that are often much dry for many other crops. On average about 2.5-3.0 tons of cotton stalks are generate for each hectare of cotton cultivation. The top four producers (China, India, U.S and Pakistan) accounted for almost 80% of the world production in 2006 (Altin, 2001). India is the world's largest cotton producer contributing about 23% of global production and the crop plays important role in the country's economy and rural livelihoods. Cotton is cultivated on around 13.07 million hectares in India and supports nearly 60 million people. Production has fluctuated in recent years, with 33 million bales in 2022–23, 31 million bales in 2021-22 and an estimated 29 million bales in 2024-25. The Central Zone, especially Gujarat, leads production, while the Southern Zone ranks 2ND with Telangana as a

key contributor. Cotton sector also supports millions of farmers and workers, making it one of the important industries after agriculture in India, with significant contributions to employment and exports(India Brand Equity Foundation, (2025).

9.1 Blockchain technology used by some organisation

Texprocil, Cotton Textiles Export Promotion Council have embraced blockchain based technology to increase the traceability of garments and fabrics made from Kasturi cotton through QR codes (Munjal, 2025).

Blockchain for Transparency Welspun utilises BCT to trace cotton back to its source farm, ensuring transparency in supply chain.The company offers farmers a minimum support price and even purchases cotton directly if there are no other buyers(Textile Value Chain. 2025).

Better Cotton Initiative conducted traceability pilot projects during 2021–2023 in cotton supply chains in India, including Kodinar in Gujarat where blockchain based and digital traceability technologies such as Textile Genesis, along with other tracking solutions, were implemented to enhance transparency and end to end traceability in the cotton supply chain (Better Cotton, 2023)

10 Practical Utility of the Research Project

The practical utility of this research lies in its ability to provide real-world solutions for improving the cotton supply chain through the use of blockchain technology. It helps farmers, small and marginal farmers, to obtain better prices by reducing the involvement of intermediaries and ensuring transparency in transactions. The study offers valuable guidance to agribusiness firms and private companies on effective implementation of blockchain systems. It also assists policymakers in developing appropriate policies and support mechanisms to encourage technology adoption. Furthermore, the research identifies key stakeholders, determinants, and challenges associated with blockchain adoption, which can help in better planning and decision-making. Overall, the study supports the development of a more efficient, transparent, reliable and sustainable agricultural supply chain system.

11. Objectives

The specific objectives of the present investigation are:

1. To examine the socio-economic profile of the sample respondents
2. To identify the key stakeholders and their roles in a blockchain-enabled cotton supply chain
3. To analyse determinants influencing the implementation of blockchain technology in cotton supply chains

4. To analyse the improvements in farmers' outcomes due to blockchain adoption in the cotton supply chain
5. To assess the challenges faced in the adoption of blockchain technology in cotton supply chain

12. Review of Literature

12.1 Stakeholders in blockchain-enabled supply chain

Ahmed and MacCarthy (2021) analysed blockchain enabled traceability in the textile apparel supply chain and highlighted its role in improving product authentication, transparency and sustainability. The study emphasized that blockchain facilitates digital identification of products and enables better tracking across different stages of the supply chain. However, it also pointed out challenges in extending traceability to upstream raw Product suppliers and downstream manufacturing networks. The authors stressed the need for clear defined objectives and appropriate design of traceability systems to ensure effective implementation and improved supply chain performance.

Wang *et al.* (2021) explored design and implement of blockchain enabled supply chains using a design science research approach. The study highlighted that blockchain improves transparency and provenance in complex supply chain networks through smart contracts. It also proposed design principles for developing effective blockchain architectures and emphasized their role in enhancing business value and coordination among supply chain actors.

Nethrayini and Nagesh (2026) analysed the cotton marketing system in India with a focus on ginning processes and marketing channel efficiency in Raichur district, Karnataka. The study compared two channels: Channel 1 (direct sale from farmers to ginning mills) and Channel II (involving APMC traders as intermediaries). Data collected from 15 ginning mill owners revealed that Channel I provides better returns to farmers with a higher share in the consumer rupee (35.40%) compared to Channel II (33.60%). Additionally, marketing efficiency, measured using Acharya's method was higher in Channel 1 (0.55) than in Channel II (0.51). The findings suggest that reducing intermediaries improves price realization for farmers and enhances all supply chain efficiency, contributing to better livelihoods and sustainable agricultural development.

12.2 Determinants influencing the implementation of BCT

Kuo *et al.* (2008) proposed a grey based Taguchi method to address multi response optimization problems in simulation modeling. The study combined Taguchi techniques with grey relational analysis (GRA) to convert multiple responses into a single response for effective

optimization. The findings demonstrated that the method provides a practical and efficient approach for solving complex simulation problems with comparable performance to existing techniques.

Alazab *et al.* (2021) investigated the determinant influencing blockchain adoption in supply chains using an integrated model combining UTAUT, TTF and ISS frameworks. Based on survey data from multiple industries, the study found ,these models positively impact employees willingness to adopt blockchain technology. However social influence was not significant, while inter organizational trust played a vital role in shaping adoption intentions. The study emphasizes the significance of trust and system effectiveness in promoting blockchain adoption in supply chains.

Karamchandani *et al.* (2021) applied a structural equation modeling (SEM) approach to analyze the role of blockchain technology in improving supply chain management and profitability in the manufacturing industry. The study found that blockchain enhances key supply chain dimensions such as visibility, trust and delivery reliability, thereby improving organizational performance. It also highlighted that factors like organizational size, IT integration and integration intensity influence adoption with smaller firms and those having higher IT integration more likely to adopt blockchain technology early.

Kumar Bhardwaj *et al*. (2021) The study explored the factors that affect blockchain adoption among SMEs in India using an integrated TAM, TOE, and DOI framework. It found that benefits like relative advantage, compatibility, technological readiness, support from top management, perceived usefulness and vendor assistance encourage adoption. On the other hand, complexity and high costs act as key obstacles. Overall, the study offers useful insights for SMEs and technology providers to support smoother and more effective adoption of blockchain in supply chains.

Malik *et al.* (2022) examined the factors influencing organizational adoption of blockchain technology using the Technology Organization Environment (TOE) framework in the Australian context. The study found that perceived information transparency, perceived risks, organizational innovativeness, learning capability, standards uncertainty and competition intensity significantly affect adoption decisions. It also confirmed the impact of perceived advantages and alignment. The results offer valuable guidance for policymakers and organizations to support strategic adoption of blockchain technology.

Ganesh *et al.* (2025) examined the applications and impacts of blockchain technology in modern business environments and found that it significantly enhances transparency, operational efficiency and customer trust. The study further revealed that operational efficiency

plays a mediating role between blockchain adoption and customer trust, highlighting blockchain as a transformative tools for improving business processes and strengthening customer confidence.

12.3 Improvements in farmers' outcomes due to blockchain adoption

Pufahl and Weiss (2009) applied a propensity score matching to evaluate the impact of agri environment programmes on farm performance. Study found that participation significantly increased cultivated area, particularly grassland and reduced the use of chemical inputs such as fertilizers and pesticides. It also revealed heterogeneous effects across farms, with those gaining higher benefits being more inclined to engage in such programmes.

Hella (2012) used partial budgeting technique to evaluate the economic impact of green manure technology in maize based farming systems. The study found that adoption of green manure significantly increased yield, reduced production costs and improve net returns compared to conventional practices. The results indicated higher incremental benefits due to increased marketable yield and savings in fertilizer and labour costs, highlighting the potential of green manure technology to enhance profitability and sustainability in maize production.

Chinaka (2016) study pointed out the potential benefits of blockchain technology in improving financial inclusion for small-scale farmers in developing economies. It explained that blockchain can support secure, transparent, and low-cost transactions, allowing farmers to use non-traditional assets like land, livestock, and harvests as collateral. It also helps build trust among stakeholders, reduces reliance on intermediaries, and improves access to credit and financial services. Overall, blockchain can enhance financial access and support the economic empowerment of small farmers.

Thejaswini and Ranjitha (2020) discussed the advantages of blockchain technology in agriculture, especially in improving supply chain transparency and data integration. The study highlighted that blockchain enables secure, decentralized, and peer-to-peer transactions, which improve food traceability and origin tracking. It also reduces the role of intermediaries, lowers costs, and strengthens trust among stakeholders. In addition, blockchain supports efficient record-keeping and helps farmers by enhancing transparency, financial access, and overall supply chain efficiency.

Cai *et al.* (2023) examined blockchain adoption in supply chain management from a risk management perspective. The study revealed that perceived advantages such as traceability, transparency, information sharing and decentralization enhance supply chain resilience and responsiveness, thereby promoting adoption intention. It also highlighted that managers with

higher uncertainty avoidance are more likely to implement blockchain technology, highlighting its role in improving risk mitigation and coordination in supply chains.

12.4 Challenges faced in the adoption of BCT

Kumar *et al.* (2019) examined the challenges faced in adoption of blockchain technology in developing countries using a questionnaire-based approach. The study found that despite the significant potential of blockchain in advancing industries, several barriers hinder its widespread adoption, particularly from a top management perspective. Addressing these challenges is essential for successful integration and can contribute positively to overall economic development.

Ghode *et al.* (2021) analysed the issues related to blockchain adoption in supply chains using interpretive structural modeling (ISM). The study recognized major challenges such as building trust among stakeholders, complying with regulatory frameworks, ensuring data transparency and security, improving coordination and information sharing and addressing societal and behavioral changes through training. It also highlighted the interrelationships among these challenges, providing insights for practitioners to effectively plan and implement blockchain technology in supply chains.

Kouhizadeh *et al*. (2021) explored the barriers to blockchain adoption in sustainable supply chains using the Technology-Organization-Environment framework and force field theory. The study found that technological and supply chain related barriers are the most critical challenges, followed by organizational and external factors. It also highlighted differences in perceptions between academics and industry practitioners regarding these barriers. The findings provide important insights into the interrelationships among barriers and support better understanding and implementation of blockchain technology in sustainable supply chains.

Paul *et al.* (2022) stated that the interpretive structural modelling approach was used to structure the causal relationships among identified critical success factors of supply chain sustainability. The study also classified these factors into cause-and-effect groups and developed a hierarchical structure to facilitate better decision-making and identification of suitable solutions.

Akella *et al.* (2023) highlighted that achieving smart and sustainable agriculture is more complex compared to other industries due to the involvement of numerous unpredictable pre and post-harvest factors. The study emphasized that integrating blockchain technology with sustainable agricultural practices can enhance transparency, trust and efficiency across the agrifood supply chain. Using the PRISMA approach, the authors systematically identified key

enablers such as stakeholder collaboration, increased customer trust and democratization of information. However, the study also revealed significant barriers, including the absence of global standards, lack of industry-level best practices, and inadequate policy frameworks.

13. Materials and Methods

A clear and systematic scientific approach is essential to achieve the study objectives and ensure accurate interpretation of results. This includes describing the study area, research design, sampling methods, types of data and data analysis techniques. Supporting information such as secondary data sources is also important for proper reference and documentation

13.1 Selection of the study area

The present study focuses on analysing the adoption of BCT in the cotton supply chain. The study will conduct in the Saurashtra region of Gujarat, which is a major cotton-producing area and has increasingly witnessed the implementation of digital technologies to enhance supply chain efficiency and traceability. Various organizations, including the Better Cotton Initiative and WelKrishi, have supported the introduction of blockchain-based solutions in the region to improve transparency and farmer engagement in the cotton value chain (Better Cotton, 2023; Textile Value Chain, 2025)

Blockchain technology has been implemented on a pilot basis in selected clusters to streamline the cotton supply chain, ensure traceability from farm to market, and create a digital identity for cotton produce. These initiatives aim to reduce intermediaries, enhance price realization, and improve trust among stakeholders (Tripoli and Schmidhuber, 2018). A significant number of stakeholders have adopted blockchain technology to examine the its benefits for farmers, and its impact on various stakeholders in the cotton supply chain.

13.2 Research design

Understanding the adoption of blockchain technology (BCT) in the cotton supply chain will require detailed interaction with various stakeholders involved in the system. Therefore, a field survey will be conducted to examine the role, impact and challenges associated with blockchain technology across different stakeholders in the cotton supply chain.A list of cotton farmers involved in blockchain technology adoption will be prepared with the help of organisation and field level verification. A total sample of 300 farmers will be selected from the district using a simple random sampling technique. The selected respondents will include both adopters and non-adopters of blockchain technology to facilitate comparative analysis.

The expert opinions will be also collected to understand the practical aspects of blockchain implementation, its benefits, determinants influencing, challenge.

13.3 Nature and sources of data

13.3.1 Primary data

The primary data for the study will be collected from selected sample respondents. Information on general demographic characteristics such as educational level, age, extension participation, farming experience, technology adoption and membership will be gathered. Data related to the actors involved in the blockchain enabled supply chain, determinants influencing, technology adoption, improvements in farmers' outcomes and challenges faced in adopting blockchain technology in cotton cultivation will be collected from blockchain adopters using a pre tested questionnaire.

In addition, non-adopters of blockchain technology will be interviewed to obtain information on their general profile, cotton cultivation practices. Both adopters and non-adopters will be included in the study to compare their profitability in cotton production and to assess the benefits of blockchain technology adoption.

Experts will clearly explain about the research and objectives of the study and expert opinion will also be collected for the study. Focus group discussion will employed to collect the information on influential determinants for blockchain technology adoption, improvements in farmers' outcomes, challenges involved in implementing blockchain technology adoption and potential opportunities for blockchain technology adoption in cotton supply.

13.3.2 Secondary data

secondary data will be collect from websites, journals, newspapers, and magazines.

14. Statistical Analysis

The data collected from the sample respondents will be properly organized before analysis. It will be coded and classified in a systematic way to make it easy to understand and interpret. After organizing the data, suitable statistical tools will be used to analyse it and draw meaningful conclusions. Both quantitative and qualitative methods will be applied based on the type of data collected. The selection of these tools will depend on the objectives of the study. The specific methods and techniques used for analysis are explained in the following section.

14.1 Descriptive Statistical Tools

Descriptive statistical tools, such as percentage analysis, will be used to examine the general characteristics of the sample respondents, including gender, age (years), education, occupation, family size, annual income, farm size, cropping pattern, awareness of blockchain technology, training attended, and membership. Percentage analysis will also be applied to

assess the socioeconomic profile of the respondents in the study.

Percentage refers to a special kind of ratio that is used in making comparisons between two or more series of data The formula used for the per centage method is:

$$P = \frac{n}{N} * 100 \quad \ldots (1)$$

Where,

P = Percentage

n = Frequency of a particular cell

N = Total number of respondents

14.2 Process flow diagram

Supply chain analysis in agriculture focuses on understanding the movement of products from production to consumption by identifying stakeholders, their roles and interrelationships. Mapping the supply chain provides insights into key nodes, processes and stakeholder linkages (Yeshiwas *et al.,* 2024). Pictures and flowcharts will be used to illustrate the supply chain stakeholders, their activities and the key processes within the blockchain technology (BCT) enabled supply chain. The study will also examine traditional supply chain practices followed by non-adopters and compare them with the pilot blockchain integrated supply chain implemented by adopters.

14.3 Structural equation modelling

Structural Equation Modelling is a multivariate statistical technique used to examine complex relationships among variables. SEM combines factor analysis and multiple regression analysis to assess the structural relationships between observed variables and latent constructs.

SEM is particularly suitable for analyse determinants influencing the implementation of blockchain technology in the cotton supply chain. SEM is a linear modelling method that examines relationships between set of observed variables and a smaller number of latent variables. The SEM framework comprises two main components. the measurement model and the structural model.

The measurement model describes the relationships between latent variables (ξ and η) and their corresponding observed indicators (X and Y) expressed as:

$$Y = \Lambda r\, \eta + \varepsilon \quad \ldots (2)$$

$$X = \Lambda x\, \xi + \delta \quad \ldots (3)$$

Where, X is a vector consists of of exogenous observation variables η indicates the endogenous latent variable and ξ indicates the exogenous latent variable; Λr represents endogenous

observed variables, born from the latent variable factor loading matrix, which represents the endogenous latent variable η and the observation of the relationship between the variable Y.

Here, Λx indicates observation of exogenous variables in the element loading matrix of the exogenous latent variables; this means an exogenous latent variable ξ is deduced and the observation of the relationship between variable X, ε and δ is the residual matrix of the measurement equation. The structural model illustrates the relationship between exogenous latent variables and endogenous latent variables. This relationship is stated graphically to form a path diagram.

$$\eta = B\eta + \Gamma\xi + \gamma \quad \ldots (4)$$

Where, B is the structure coefficient matrix, which indicates the structure model of endogenous latent variable η and the composition of the fector that influence each other. Γ is the structure coefficient matrix which indicates exogenous latent variable ξ in the model of the factors influence on endogenous latent variable η ; γ is the residual matrix of the structural model. The empirical equation for the estimation of blockchain technology adoption is given as:

$$BCTADP = \beta_0 + \beta_1 DTRANS + \beta_2 PU + \beta_3 TMS + \beta_4 CC + \beta_5 PEU + \beta_6 SO + \beta_7 GOVT + \beta_8 RBA + \delta \quad \ldots (5)$$

Where,

BCTADP = Blockchain Technology Adoption

DTRANS = Data Transparency

PU = Perceived Usefulness

TMS = Top Management Support

CC = Cost Concerns

PEU = Perceived Ease of Use

SO = Scientific Orientation

GOVS = Government Support

RBA = Risk Bearing Ability

In this model, the selected latent constructs include data transparency, top management support(TSM), cost concerns, perceived ease of use, scientific orientation, perceived usefulness, government support and risk bearing ability. These constructs and its measurement items will adapted from earlier studies (Bhardwaj *et al.,* 2021).

All variables were measured using a five-point Likert scale ranging from “1 = strongly disagree” to “5 = strongly agree” to analyse determinants influencing the implementation of blockchain technology, based on these variables, a conceptual framework was developed. The

proposed hypotheses will test using SEM through Amos software to identify the key determinants influencing blockchain technology adoption in cotton supply chain.

14.4 Grey Relational Analysis(GRA)

GRA introduced by Ju-Long (1982), is a technique developed to model systems characterized by incomplete and uncertain information. It is widely used for analysing complex decision-making problems where data is insufficient or ambiguous. GRA is an effective evaluation method for developing a reliable model by incorporating influencing determinants of blockchain technology, particularly in uncertain and complex supply chain (SC) networks (Luthra et al., 2018). It helps in determining the relative benefits of each determinant and forecasting their impact on blockchain adoption by utilizing expert judgments. This method is especially useful for ranking the influencing determinants affecting the implementation of blockchain technology in cotton supply chains. The GRA methodology involves five key steps:

- Formation of a decision matrix
- Grey relational generation
- Reference sequence generation
- Grey relational coefficient calculation
- Grey relational grade calculation

14.4.1 Decision Matrix

Expert opinion was gathered on a five- point Likert scale ranging from '5' strongly agree to '1' strongly disagree, for the eight influential elements. The decision matrix will create based on the information gathered from experts' opinions. The constructed decision matrix are given in the equation 1.

$$A = \begin{bmatrix} X11 & \dots & X1n \\ \vdots & \ddots & \vdots \\ Xm1 & \dots & Xmm \end{bmatrix} \quad \dots (6)$$

Where, rows (X11 …X1n) n - indicates experts ratings opinion and in columns (X11 …Xm1) m-indicates the factors. Here Xij $(1 \leq i \leq m, 1 \leq j \leq n)$ denotes the ith data sequence's evaluation value in relation to factor j.

14.4.2 Grey relational generation (GRG)

GRG is a normalization process. Under normalization process, all the determinants are processed into comparable sequences.

$$X11 = \frac{\boldsymbol{Y11 - min(xi1)}}{\boldsymbol{max(Yi1) - min(Yi1)}} \quad \dots (7)$$

$$Xm1 = \frac{ym1 - min(xi1)}{max(Yi1) - min(Yi1)} \qquad (i=6,7\ldots m) \qquad \ldots (8)$$

14.4.3 Sequence generation matrix

After the normalisation process, all factors will define in between the range [0, 1] in the reference sequence generation process. The influences of alternative i will the most appropriate for attribute j, if the value Xij with an attribute j of alternative equals 1. Hence reference sequence was written as,

$$Xoj = [1\ 1\ 1\ 1\ 1] \qquad \ldots (9)$$

14.4.4 Calculating grey relational coefficient

To find the variation between the comparison sequence and the reference sequence, the grey relational coefficient is calculated using the following formula:

$$\Delta ij = |X0j - Xij| \qquad \ldots (10)$$

$$r(X0j, Xij) = \frac{(\Delta min + t\Delta max)}{(\Delta ij + t\Delta max)} \qquad \ldots (11)$$

Here t = 0.5, t value was used for expanding and compressing the range of grey relational coefficient.

14.4.5 Grey relational grade calculation

As per Tosun (2006) Grey relational grade will be referred as the numerical measure of relevancy between two sequences ie., reference sequence and a comparability sequence.

$$\mathrm{r(X0, Xi)} = \sum_{j=1}^{n} Wjr(Xoj, Xij) \qquad \ldots (12)$$

Wj is the weight of attribute j and it depends on how the decision maker judges a certain problem. The best alternative is one whose value similar to the reference value. The selected factor will have a maximum value of GRG, which represents the higher influence of all determinants on the implementation of blockchain technology in agriculture.

14.5 Partial Budgeting Techniques

Partial budgeting analysis will be conducted using a standard blank partial budget format suggested by (Daku *et al.,* 2012). This method, often considered a simplified form of marginal analysis, focuses on evaluating the changes in costs and returns resulting from a small or specific change in farming practices.

It is widely used to assess the economic feasibility of adopting new technologies in agriculture. In this study, partial budgeting will apply to examine the financial implications of adopting blockchain technology by farmers.

The analysis estimates the net improvements outcomes by comparing the additional costs incurred and additional returns gained due to the adaptation of blockchain technology. This approach helps to identify whether the adaptation of blockchain technology is economically viable for farmers. Specifically, the net gain from i adopting blockchain technology in cotton cultivation was calculated using this method.

14.5.1 Proposed change

Partial budgeting technique will used to calculate the changes in cost reduction and income, for adopters and non-adopter farmers of blockchain technology in cotton.

Table 14.1 Change in method of Production

Debit (A)	Credit (B)
Added cost ---------- Rs ---------- ---------- Rs ---------- Reduced revenue ---------- Rs ---------- ---------- Rs ----------	Added returns ---------- Rs ---------- ---------- Rs ---------- Reduced cost ---------- Rs ---------- ---------- Rs ----------
Total added cost and reduced return (A) Rs ---------	Total added returns and reduced cost (B) Rs ---------
Net gain=B – A	

14.6 Propensity Score Matching Approach

Rosenbaum and Donald, (1983) The conditional chance of receiving treatment based on pretreatment variables is known as the propensity score. It acts as a balance score to guarantee that the distribution of observed variables in the treated and untreated groups is comparable. People observed traits become similar when they have the same propensity score (McCaffrey et al., 2004).

Logistic or probit regression models are frequently used in practice to estimate propensity scores, with probit regression being the most popular. The influence of blockchain technology on cotton production will be assessed in this study utilizing a probit regression model and the Propensity Score Matching (PSM) technique, specifically the Average Treatment on the Treated (ATT) method.

Steps in estimating propensity score matching

Propensity score matching (PSM) involves four main steps: selecting observed variables, choosing a model to estimate propensity scores, deciding on matching criteria, and estimating treatment effects (Caliendo and Kopeinig, 2008).

i. The propensity scores will estimate using the probit regression model to find the probability of BCT adoption by sample respondents.
ii. The second step will identify the area of common support and the results with equal covariates between two groups confirms that blockchain technology adopters and non-adopters had common support.
iii. The third step will a score matching principle where blockchain technology adopters were matched with non-adopters use propensity scores that indicates the probability of blockchain technology adoption based on the observed variables.
iv. Finally, the mean difference in outcome between the two matched groups will calculated. The findings indicate the impact of blockchain technology adoption on household farm income based on the surveyed sample respondents.

Based on Becker and Ichino theory (2002) the treatment effect analysis of BCT adoption can be modelled as follows:

$$i = \alpha Xi + \beta Ti + \varepsilon i \quad \ldots (13)$$

Here, Yi represents the outcome for household i, where Yi (1) indicates adopters and Yi (0) indicates non-adopters. Xi denotes the set of selected observed variables for household i. Ti is a dummy variable taking the value 1 for adopters and 0 for non-adopters. εi is the error term, capturing unobserved factors that influence Yi. For each household the difference (δi) between treated and untreated outcomes shows the unobserved treatment effect, expressed as:

$$\delta i = Y1i - Y0i \quad \ldots (14)$$

Here, ATT (Average Treatment Effect on the Treated) refers to the average gain in outcomes of adopters compared to non-adopters. It is expressed as:

$$ATT = E\left(\frac{Yi(1)}{T} = 1\right) - E\left(\frac{Yi(0)}{T} = 1\right) \quad \ldots (15)$$

Where Yi is the outcome for household i and T is the treatment dummy. Yi (1) represents the outcome for adopters, while Yi (0) represents the outcome for non-adopters. In simple terms, ATT can be written as:

$$ATT = E\left(\frac{Yi - Y0}{T} = 1\right) \quad \ldots (16)$$

The empirical model used in the study is given as:

$$Y = \alpha + \beta 1X1 + \beta 2\ X2 + \beta 3X3 + \beta 4X4 + \beta 5\ X5 + \beta 6\ X6 + \beta 7\ X7 + \beta 8\ X8 + \beta 9\ X9 + \beta 10\ X10 + \beta 11\ X11 + \varepsilon i$$

Where,

X_1 = Age
X_2 =Gender

X_3 = Family type

X_4 = Educational status

X_5 = Farming experience

X_6 = Crop Income

X_7 = Farm Size

X_8 = Crop yield

X_9 = Extension agency contact

X_{10} = Training programme attended

X_{11} = Access to technological information

The causal effect of BCT adoption on farm income will estimated using the nearest neighbour matching method through the psmatch2 command in STATA 16 platform.

14.7 Garrett's ranking technique

Garrett's ranking technique will be used to analyze the challenges in technology adoption. The ranks given by respondents will be converted into percent positions using the following formula:

$$\text{Percent Position} = \frac{\mathbf{100(Rij - 0.05)}}{\mathbf{Nj}}$$

Where,

Rij = Rank given for ith attribute by jth individual

Nj = Number of attributes ranked by jth individual

The percent positions will then be converted into scores using Garrett's table. Mean scores will be calculated for each attribute. Finally, the attributes will be arranged in descending order based on their mean scores and the attribute with the highest mean score will be given the first rank and identified as the most important challenge in blockchain adoption in agricultural supply chains.

14.8 Interpretive structural modelling approach

Interpretive Structural Modelling (ISM) will be used to examine the interrelationships among the selected variables and to develop a hierarchical structure. It is a widely applied method for modelling key constructs and analyzing their relationships (Gardas et al., 2019).

Key barriers or constructs related to blockchain technology implementation in the cotton supply chain will be identified through expert opinions and literature review. These identified

constructs will then be analyzed using an integrated ISM approach which helps in understanding both the relationships and the strength of influence among them.

ISM simplifies complex problems by organizing them into a clear hierarchical structure. Due to its advantages over other multi-criteria decision-making methods, ISM has been widely used across various fields to study and model complex issues (Attri et al., 2017).

The steps will be involved in ISM approach will be presented in below.

- Identification of barrier using literature review and experts' opinion
- Developing interrelationship using self-structural interaction matrix
- Quantifying the established relationship with initial and final reachability matrix
- Level portioning through iterative procedure
- Creating ISM structure to identified barriers
- Grouping through MICMAC analysis

14.8.1 Identification of barriers

Barriers will be identified through the literature review and experts opinion. Most important and influential barriers will be taken to construct the model.

14.8.2 Self-structural interaction matrix

A structural self interaction matrix will constructed to define the contextual relationship between the identified barriers. At first, the barriers (factors) were arranged in rows (i) and columns (j). Then, pair wise contextual relationships between factor i and factor j were identified based on experts' opinions. The established relationship between the identified barriers will be represented using the symbols V, A, X, O. If the factor i influence the factor j then the symbol V will used for representation, symbol A denotes that factor j influence factor i. when both factors i and j influence each other, it was represented as X and if there will no relationship between the factors i and j, it was represented as O.

14.8.3 Initial and final reachability matrix

The self-structural interaction matrix (SSIM) will be converted into an initial reachability matrix (IRM), where the relationships between factors are transformed into binary values (0 and 1) using specific rules. The IRM will then be checked for transitivity to obtain the final reachability matrix (FRM).

According to the transitivity rule, if factor i influences factor j and factor j influences factor k, then factor i indirectly influences factor k. Thus, factors i and k have an indirect relationship.

14.8.4 Level partioning

The final reachability matrix will be used for different level partition and hierarchy formation. For level partitioning, the final reachability matrix will split into three sets: the reachability set, the antecedent set, and the intersection set. This will be accomplished in order to determine the hierarchical relationship between the variables. The reachability set consisted of the variable and other variables that contributed to its achievement. Antecedent set includes the variable and the other variables to which it helped to happen. Intersection set consisted of common variables from both the reachability set and the antecedent set. Further when the reachability set and intersection set will similar, then that particular variables will identify as the first phase or first level. Then those variables will removed from the partioning process. The same procedure will be repeat until the lowest level of ISM structure will be identified.

14.8.5 Creating ISM Structure

Level partitioning will used to build the ISM structure. It will a pictorial representation about interrelationship between the identified barriers in hierarchical way. the ISM structure illustrated the connection between the barriers. This provided the conceptual framework for the barriers for elimination while adopting the technology.

15. References: